DTU Library

Application of Advanced Particle Swarm Optimization Techniques to Wind-thermal Coordination

Singh, Sri Niwas; Østergaard, Jacob; Yadagiri, J.

Published in:
15th International Conference on Intelligent System Applications to Power Systems, 2009. ISAP '09

Link to article, DOI:
10.1109/ISAP.2009.5352912

Publication date:
2009

Document Version
Publisher's PDF, also known as Version of record

Citation (APA):
Singh, S. N., Østergaard, J., & Yadagiri, J. (2009). Application of Advanced Particle Swarm Optimization Techniques to Wind-thermal Coordination. In *15th International Conference on Intelligent System Applications to Power Systems, 2009. ISAP '09* (pp. 1-6). IEEE. https://doi.org/10.1109/ISAP.2009.5352912

Application of Advanced Particle Swarm Optimization Techniques to Wind-thermal Coordination

S.N Singh, J. Østergaard and J. Yadagiri

Abstract—New and renewable energy sources are being explored and utilized due to the rise of environmental concerns and progressive extinction of traditional fossil energy sources. Wind power generation is one of such sources and is extensively integrated in the existing power systems. Development of better wind-thermal coordination algorithm is necessary to determine the optimal proportion of wind and thermal generator capacity that can be integrated into the system. In this paper, four versions of Particle Swarm Optimization (PSO) techniques are proposed for solving wind-thermal coordination problem. A pseudo code based algorithm is suggested to deal with the equality constraints of the problem for accelerating the optimization process. The simulation results show that the proposed PSO methods are capable of obtaining higher quality solutions efficiently in wind-thermal coordination problems.

***Index Terms*-- Economic dispatch, Particle Swarm optimization, Wind-thermal coordination**

I. Nomenclature

a_i, b_i, c_i	Cost coefficients
C, w	Constriction and inertia weight factors.
c_1, c_2	Cognitive and social coefficients
d	Percentage of maximum unit capacity
$DR_i^{\max}$, $DS_i^{\max}$	Maximum ramp-down rate and down reserve contribution of i^{th} thermal unit
DRW	Down spinning reserve requirement considering wind power generation.
$DS_i(t)$	Down reserve contribution of i^{th} thermal unit at hour t
F_T	Total operation cost during period T
$gbest$	Global best position
$I_i(t)$	Schedule state of i^{th} thermal unit for hour t
i, j	Index for thermal and wind units, respectively
NT, NW	Number of thermal and wind units, respectively
$pbest$	Local best position
$P_i(t)$	Generation of i^{th} thermal unit at hour t
$P_{i,r}^{\max}$	Upper generation limit of i^{th} thermal unit
$P_i^{\max}(t)$, $P_i^{\min}(t)$	Maximum and minimum generation, respectively of i^{th} thermal unit at hour t
$P_{i,r}^{\min}$	Lower generation limit of i^{th} thermal unit
$P_L(t)$	System load demand at hour t
$P_{Wj}^{\max}$	Upper generation limit of j^{th} wind unit
$P_{Wj}(t)$	Actual generation of j^{th} wind unit at hour t
$P_{Wj}^*(t)$	Available generation of j^{th} wind unit at hour t
$P_{WT}(t)$	Total actual wind generation at hour t
$P_{WT}^*(t)$	Total available wind generation at hour t
$rand_1$, $rand_2$	Random numbers between 0 and 1
SR_i	Startup ramp rate limit of i^{th} thermal unit
STC_i	Startup cost of i^{th} thermal unit
T	Number of time intervals (hours)
$TDR(t)$	System ramping down capacity at hour t
$t_{OFF,i}(t)$	Down period of i^{th} thermal unit till time t
$T_{OFF,i}$	Minimum down time of i^{th} thermal unit
$T_{ON,i}$	Minimum up time of i^{th} thermal unit
$T_{ON,i}(t)$	Up period of i^{th} thermal unit at time t
$TUR(t)$	System ramping up capacity at hour t
$UR_i^{\max}$	Maximum ramp-up rate of i^{th} thermal unit
URW	Up spinning reserve requirement considering wind power generation.
$US_i(t)$	Up reserve contribution of i^{th} thermal unit at t
$US_i^{\max}$	Maximum up reserve contribution of i^{th} thermal unit
USR_B	System up spinning reserve requirements not considering wind power generation
v_i	Velocity of the i^{th} particle
$v(t)$	Wind speed at hour t
$v_{I.j}$, $v_{o.j}$	Cut-in and cut-out wind speed of jth wind unit
$v_{R.j}$	Rated wind speed of j^{th} wind unit
x_i	Position of the i^{th} particle
α, β	Coefficients of additional up (or down) reserve requirement (second-order model).
γ	Coefficient of additional up/ down reserve requirement (linear model)

S.N. Singh (email: sns@iitk.ac.in) and J. Ostergaard (email: joe@elektro.dtu.dk) are with the Department of Electrical Engineering, Denmark Technical University, Denmark. J. Yadagiri is with the department of Electrical Engineering, IIT Kanpur, India. Dr SN Singh is on leave from Indian Institute of Technology Kanpur-208016, India.

978-1-4244-5098-5/09/$26.00 ©2009 IEEE

II. INTRODUCTION

WITH the increase in fuel prices, environmental concerns, and reduction in wind-turbine generating system cost, the integration of wind power generation in the power system having conventional power generators is increasing. Due to intermittency and unpredictable nature of wind, the wind power generation is not reliable and also it creates difficulty in the control of frequency and scheduling of generation. Therefore, the determination of optimal wind power generation, which can be integrated in to the emerging power system, is very important. Electricity generated from wind power can be highly variable at several different timescales: from hour to hour, daily, and seasonally. Annual variation also exists, but it is not very significant. Because of instantaneous electrical generation and consumption must remain in balance to maintain grid stability, this variability presents substantial challenge to incorporating large amounts of wind power into a grid system.

Due to uncertain nature of wind power, it is widely believed that large wind power penetration would put an increased burden on the system operation. In general, the largest proportion of the emergency reserve is carried to cover the loss of the largest generation unit in the system. However, with increasing wind power penetrations in power systems, scheduling of additional emergency reserve will be needed to maintain an adequate level of supply security. Apart from the up spinning reserve requirements, there are strong demand for enough down spinning reserve requirements to satisfy the sudden rise of wind power generation during low system load requirement to avoid the forced shutdown of thermal generating units. Therefore, taking all these considerations, more advanced algorithms are needed for solving the wind-thermal coordination problem.

The unit commitment is one of the key functions of modern energy management system and this problem is formulated as a constrained optimization problem with the objective of generation allocation to the power generators to minimize the total cost with satisfaction of all operating constraints. This problem is further complicated by the wind-thermal coordination scheduling imposed by the adding of additional reserve requirements. Because of strong coupling between system spinning reserve requirements and the total actual wind power generation, both of them should be consider at the same time, it is very difficult to solve the wind-thermal coordination problem

Conventional methods [1-4] usually assume the input-output characteristics of power generators, known as cost curves to be quadratic or piecewise quadratic, monotonically increasing functions. But modern generating units have a variety of non-linearities in their cost curves due to valve point loading and other effects, which make this assumption inaccurate and resulting approximate solutions cause a lot of revenue loss overtime. On the other hand, evolutionary methods such as Genetic Algorithms (GA) [5] and Particle Swarm Optimization (PSO) are free from convexity assumptions and perform better due to their excellent parallel search capability. Hence, they are particularly popular for solving such nonlinear, non-convex, discontinuous optimization problems.

The wind-thermal unit commitment solution methods reported in the literature include Simulated Annealing [6], Hybrid Dynamic Programming [7], and Fuzzy Mixed Integer Linear programming [8] techniques. In this paper, four modified versions of particle swarm optimization techniques are used to find the optimal proportion of wind generation capacity that can be integrated into the existing power system and the results of the proposed algorithm for a test system are reported. A new pseudo code based algorithm is developed, in this paper, for equality constraints other than the penalty function methods [9-12].

III. PROBLEM FORMULATION

The main objective of wind-thermal scheduling problem is to minimize the total fuel cost of thermal generating units with optimal integration of wind energy into existing power system, while simultaneously satisfying all constraints. The problem formulation is the same as reported in the literature [7].

$$Minimize \quad F_T = \sum_{t=1}^{T}\sum_{i=1}^{NT}[I_i(t)\times F_i(P_i(t)) + I_i(t)\times(1-I_i(t-1)\times STC_i] \quad (1)$$

Subject to following constraints:

1) System constraints

a) Power balance constraint (losses are neglected)

$$\sum_{i=1}^{NT} I_i(t)\times P_i(t) + P_{WT}(t) = P_L(t) \quad (2)$$

b) System up/down spinning reserve requirements

$$\sum_{i=1}^{NT} I_i(t)\times US_i(t) \ge USR_B + URW(P_{WT}(t)) \quad (3)$$

$$\sum_{i=1}^{NT} I_i(t)\times DS_i(t) \ge DRW(P_{WT}(t)) \quad (4)$$

c) Minimum/maximum thermal plant output constraints

$$P_L(t) - P_{WT}(t) \ge DRW(P_{WT}(t)) + \sum_{i=1}^{NT} I_i(t)\times P_{i.r}^{\min}(t) \quad (5)$$

$$\sum_{i=1}^{NT} I_i(t)\times P_i^{\max}(t) + P_{WT}(t) \ge P_L(t) + USR_B + URW(P_{WT}(t)) \quad (6)$$

2) Thermal generator constraints

a) Unit's maximum up/down reserve contribution constraints

$$US_{\mathrm{i}}^{\max} = d\times P_{i.r}^{\max} \quad \text{and} \quad DS_{\mathrm{i}}^{\max} = d\times P_{i.r}^{\max} \quad (7)$$

b) Unit's up/down reserve contribution constraints:

$$US_{\mathrm{i}}(t) = \min(US_{\mathrm{i}}^{\max}, P_{i.r}^{\max} - P_i(t)) \quad (8)$$

$$DS_{\mathrm{i}}(t) = \min(DS_{\mathrm{i}}^{\max}, P_i(t) - P_{i.r}^{\min}) \quad (9)$$

c) Unit's ramping up/down capacity constraints:

$$UR_{\mathrm{i}}(t) = \min(UR_{\mathrm{i}}^{\max}, P_{i.r}^{\max} - P_i(t)) \quad (10)$$

$$DR_{\mathrm{i}}(t) = \min(DR_{\mathrm{i}}^{\max}, P_i(t) - P_{i.r}^{\min}) \quad (11)$$

d) Unit generation limits

$$P_i^{\min}(t)\times I_i(t)\le P_i(t)\le P_i^{\max}(t)\times I_i(t) \quad (12)$$

$$P_i^{\max}(t)=\min\{P_{i.r}^{\max},P_i(t-1)+UR_i^{\max}\} \quad \text{if } I_i(t)=I_i(t-1)=1$$
$$=\min\{P_{i.r}^{\max},P_i(t-1)+SR_i\}, \quad \text{if } I_i(t)=I_i(t-1)=0 \quad (13)$$

$$P_i^{\min}(t)=\max\{P_{i.r}^{\min},P_i(t-1)-DR_i^{\max}\}, \quad \text{if } I_i(t)=I_i(t-1)=1$$
$$=P_{i.r}^{\min}, \quad \text{if } I_i(t)=I_i(t-1)=0 \quad (14)$$

e) Minimum up/down time constraints:

$$[t_{ON,i}(t-1)-T_{ON,i}]\times I_i(t-1)-I_i(t)\ge 0 \quad (15)$$

$$[t_{OFF,i}(t-1)-T_{OFF,i}]\times I_i(t-1)-I_i(t)\ge 0 \quad (16)$$

3) Wind generator constraints:

a) Wind generation fluctuation constraints:

$$P_{WT}(t)-P_{WT}(t-1)\le TDR(t).\ \mathit{if}\ P_{WT}(t-1)\le P_{WT}(t) \quad (17)$$

$$P_{WT}(t-1)-P_{WT}(t)\le TUR(t).\ \mathit{if}\ P_{WT}(t-1)\ge P_{WT}(t) \quad (18)$$

b) Wind power curve constraints:

$$P_{W.j}^{*}(t)=0, \quad v(t)\le v_{I.j} \quad or \quad v(t)>v_{o.j}$$
$$=\varphi_j(v(t)), \quad v_{I.j}\le v(t)<v_{R.j}$$
$$=P_{W.j}^{\max}, \quad v_{R.j}\le v(t)<v_{O.j} \quad (19)$$

c) Total available wind generation

$$P_{WT}^{*}(t)=\sum_{j=1}^{NW}P_{W.j}^{*}(t) \quad (20)$$

d) Total actual wind generation limit:

$$0\le P_{WT}(t)\le P_{WT}^{*}(t) \quad (21)$$

IV. Wind-Thermal Coordination Scheduling Algorithm

The time horizon is divided into smaller time stages, normally of one hour each. The wind-thermal coordination algorithm proposed in this paper is divided in three modules.

A. Wind Module

In this module, the maximum wind power generation and the spinning reserve requirements for wind power generation is calculated. The maximum wind power penetration level will be given by applying the following equations

$$P_{WT}(t)=\min\{P_{WT}^{*}(t),P_{WT1}(t),P_{WT2}(t),P_{WT3}(t)\} \quad (22)$$

where

$$P_{WT1}(t)=\frac{\sum_{i=1}^{NT}US_i(t)-USR_B}{\gamma} \quad (23)$$

$$P_{WT2}(t)=\frac{P_L(t)-\sum_{i=1}^{NT}I_i(t)\times P_i^{\min}(t)}{1+\gamma} \quad (24)$$

$$P_{WT3}(t)=\frac{\sum_{i=1}^{NT}I_i(t)\times DS_i(t)}{\gamma} \quad (25)$$

However, the wind power generation of a state using (22) will be invalid if the increase in WTG's power output is greater than the system ramping capacity, i.e.

$$P_{WT}(t)=P_{WT}(t-1)+TDR(t) \quad (26)$$

Since, there is no other means of increasing the output of WTG's, the infeasible state will be eliminated. When the system ramping up capacity cannot absorb the WTG's power output then the power output of wind turbine generator will decrease.

The uncertainty posed by wind-power generation requires the scheduling of additional generation reserve to compensate for possible fluctuations in output, both up and down. Because of the relationship between the system spinning reserve requirements and total actual wind power generation, both of them should be considered at the same time. In this paper, for modeling up/down spinning reserve requirements the same models are considered [7].

1) Linear Model:

$$URW(P_{WT}(t))=\gamma\times P_{WT}(t) \quad (27)$$

$$DRW(P_{WT}(t))=\gamma\times P_{WT}(t) \quad (28)$$

2) Second-Order model

$$URW(P_{WT}(t))=\alpha\times P_{WT}(t)+\beta\times P_{WT}^2(t) \quad (29)$$

$$DRW(P_{WT}(t))=\alpha\times P_{WT}(t)+\beta\times P_{WT}^2(t) \quad (30)$$

B. Pseudo Code Algorithm for Equality Constraints

A pseudo code based algorithm is developed to deal with equality constraints other than penalty function methods. The main disadvantage of penalty function methods is, when the problem is highly constrained, the search space reduces and algorithm will spend a lot of time to find feasible solutions, whereas in proposed method, a repairing process is carried on in which an infeasible solution is repaired and converted to a feasible solution there by search space increases. The computation method of proposed scheme is show as follows.

Step 1: Prepare the list for thermal units which are committed and not hitting their upper limit and total number of such unites are N_{UC}

Step 2: Prepare the list for thermal units which are committed and not hitting their lower limit and total number of such unites are N_{LC}

Step 3: Calculate the generation gap

$$P_{gap}=P_L-P_{WT}-\sum_{i=1}^{NT}P_i \quad (31)$$

Step 4: If P_{gap} is positive, continue ,otherwise go to step 6

Step 5: Calculate $P_{incr}=P_{gap}/N_{UC}$

Step 5.1: Initialize $i=1$

Step 5.2: If $i\ne N_{UC}$ continue otherwise go to step 5.7

Step 5.3: $P_i=P_i+P_{incr}$

Step 5.4: If $P_i\ge P_i^{\max}$ continue otherwise go to step 5.6

Step 5.5: Set $P_i = P_i^{\max}$ and remove this unit from the increment unit list and $N_{UC} = N_{UC} - 1$

Step 5.6: $i = i + 1$ and go to step 5.2

Step 5.7 Calculate the generation gap

$$P_{gap} = P_L - P_{WT} - \sum_{i=1}^{NT} P_i$$

Step 5.8: If P_{gap} is less than tolerance ($\varepsilon = 10^{-6}$) go to step-7 otherwise go to step-4.

Step 6: Calculate $P_{dicr} = \dfrac{P_{gap}}{N_{LC}}$

Step 6.1: Initialize $k = 1$

Step 6.2: If $k \neq N_{LC}$ continue otherwise go to step 6.7

Step 6.3: $P_i = P_i + P_{dicr}$

Step 6.4: If $P_i \geq P_i^{\max}$ continue otherwise go to step 6.6

Step 6.5: Set $P_i = P_i^{\min}$ and remove this unit from the decrement unit list and $N_{LC} = N_{LC} - 1$

Step 6.6: $k = k + 1$ and go to step 6.2

Step 6.7 Calculate the generation gap using (31)

Step 6.8: If P_{gap} is less than tolerance ($\varepsilon = 10^{-6}$) continue otherwise go to step 4.

Step 7: Stop

C. PSO Module

Particle Swarm Optimization (PSO) refers to a relatively new family of algorithms that may be used to find optimal solutions to numerical and qualitative problems. PSO was introduced by Russell Eberhart and James Kennedy in 1995 inspired by social behavior of birds flocking or fish schooling. It is easily implemented in most programming languages and has proven to be both very fast and effective when applied to a diverse set of optimization problem

In PSO, the particles are "flown" through the problem space by following the current optimum particles. Each particle keeps tracks of its coordinates in the problem space, which are associated with the best solution (fitness) that it has achieved so far. This implies that each particle has memory, which allows it to remember the best position on the feasible search space that has ever visited. This value is commonly called as $pbest$. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighborhood of the particle. This location is commonly called as $gbest$.

The position and velocity vectors of the i[th] particle of a d-dimensional search space can be represented as $X_i = (x_{i1}, x_{i2}, ...x_{id})$ and $V_i = (v_{i1}, v_{i2}, ...v_{id})$ respectively. On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as $pbest_i = (P_{i1}, P_{i2}, ...P_{id})$. If the g^{th} particle is the best among all particles in the group so far, it is represented as $gbest = pbest_g(P_{g1}, P_{g2}, ..P_{gd})$. The particle tries to modify its position using the current velocity and the distance from $pbest$ and $gbest$. The modified velocity and position of each particle for fitness evaluation in the next iteration are calculated using the following equations

$$v_{id}^{k+1} = w \times v_{id}^{k} + c_1 \times rand_1 \times (pbest_{id} - x_{id}^{k}) + c_2 \times rand_2 \times (gbest_{gd} - x_{id}^{k})$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}$$

where, w is the inertia weight parameter, which controls the global and local exploration capabilities of the particle. c_1, c_2 are cognitive and social coefficients and $rand_1$ and $rand_2$ are random numbers between 0 and 1. For the proposed method $c_1 = 2, c_2 = 2$. A large inertia weight factor is used during initial exploration and its value is gradually reduced as the search proceeds. The concept of time-varying inertial weight (TVIM) is given by

$$w = (w_{\max} - w_{\min}) \times \frac{iter_{\max} - iter}{iter_{\max}} + w_{\min}$$

$$w_{\max} = 0.9; w_{\min} = 0.4$$

where $iter_{\max}$ (=100) is the maximum number of iterations.

1) PSO with constriction factor

To improve the convergence of PSO algorithm, a constriction factor is introduced.

$$v_{id}^{k+1} = C \times [w \times v_{id}^{k} + c_1 \times rand_1 \times (pbest_{id} - x_{id}^{k}) + c_2 \times rand_2 \times (gbest_{gd} - x_{id}^{k})]$$

where, $C = \dfrac{2}{|2 - \phi - \sqrt{\phi^2 - 4}|}$ where $4.1 \leq \phi \leq 4.2$

As ϕ increases, the factor C decreases and convergence becomes slower because population diversity is reduced.

2) Crazy PSO

To handle the problem of premature convergence in PSO, the concept of craziness is used. The idea is to randomize the velocities of some of the particles, referred to as "crazy particles", selected by applying a certain probability. The probability of craziness ρ_{cr} is defined as a function of inertia weight,

$$\rho_{cr} = w_{\min} - \exp(-\frac{w^k}{w_{\max}})$$

Then velocities of particles are randomized as per the following logic.

$$v_{ik} = rand(0, v_{\max}); \quad if \quad \rho_{cr} > rand(0,1)$$

$$= v_{ik}; \quad \text{Otherwise}$$

3) New PSO

Here cognitive component is split into two different components, $pbest$ and $pworst$ i.e, the particle is made to remember not only its previous best position but also its previous worst position, while calculating its new velocity. The knowledge about the worst position helps the particle in avoiding its worst position. The velocity vector computed as:

$$v_{id}^{k+1} = C \times [w \times v_{id}^{k} + c_{1g} \times rand_1 \times (pbest_{id} - x_{id}^{k}) + c_{1b} \times rand_2 \times (x_{id}^{k} - pworst_{id}) + c_2 \times rand_2 \times (gbest_{gd} - x_{id}^{k})$$

The acceleration coefficient c_{1g} helps to accelerate the particle towards its previous best position while c_{1b} helps to accelerate the particle away from its worst position. This new feature lends additional exploration capability to the swarm.

V. Simulation results

To examine the effectiveness of the proposed method, a ten-thermal unit test system is considered. The system unit data and load demand are given in Table-I and Table-II [6]. Results of hybrid dynamic programming (HDP) are compared with normal particle swarm optimization (PSO), particle swarm optimization with constriction factor (PSOC), crazy particle swarm optimization (CPSO) and new particle swarm optimization (NPSO).

TABLE-I
LOAD DEMAND (MW) FOR 24 HOURS

Hour	Load	Hour	Load	Hour	Load
1	2000	9	1510	17	1260
2	1980	10	1410	18	1380
3	1940	11	1320	19	1560
4	1900	12	1260	20	1700
5	1840	13	1200	21	1820
6	1870	14	1160	22	1900
7	1820	15	1140	23	1950
8	1700	16	1160	24	1990

TABLE II
SYSTEM UNIT DATA

Unit No	$P_{i,r}^{\max}$, MW	$P_{i,r}^{\min}$, MW	a_i \$/MW^2	b_i \$/MW	c_i \$	STC_i \$	$T_{ON,i}$ h	$T_{OFF,i}$ h	Initial Status,h	Initial Power, \$/MW
1	60	10	0.0051	2.2034	15	10	3	2	-20	0
2	80	20	0.0040	1.9161	25	12	3	5	-20	0
3	100	30	0.0039	1.8518	40	12	2	2	-10	0
4	120	25	0.0038	1.6966	32	13	3	2	10	80
5	150	50	0.0021	1.8015	29	11	3	2	10	100
6	280	75	0.0026	1.5354	72	18	6	6	10	120
7	320	120	0.0029	1.2643	49	13	8	2	10	300
8	445	125	0.0015	1.2163	82	15	10	5	20	400
9	520	250	0.0013	1.1954	105	14	12	7	20	500
10	550	250	0.0014	1.1285	100	20	12	3	20	500

Three different studies are conducted as follows:

Study-1: Ramp rate of thermal units and spinning reserves of system are not considered. No wind generations (WGs) are considered.

Study-2: Ramp rate of thermal units and spinning reserves of system are considered. No WGs are considered.

Study-3: Ramp rate of thermal units and spinning reserves of system are considered. WG is considered.

A. *Study-1:*

The problem formulated in section III has been solved with HDF and various version of PSO. Table-III shows the comparison of results of the proposed methods with HDP [7] for study-1. It can be seen that all the method are giving the same cost and the time of computations are different. The simulation time taken by crazy PSO is less compared to HDP and other versions of PSO. The committed units are same for HDP and PSO's.

B. *Study-2*

In this case, the same 10-unit thermal system is considered with no wind generator, however, the ramp rate constraints of the thermal generating units are taken into account and the spinning reserve requirements of the system are also considered. The system up-spinning reserve assumed to be 300 MW. Table III shows the comparison of results of the proposed methods with HDP [7] for this case. The results of this example show that the proposed versions of PSO give a better cost value and take less simulation time compared to HDP. Among the proposed versions of PSO the simulation time is less for crazy PSO.

TABLE-III
TOTAL COST AND SIMULATION TIME OF STUDIES- 1 AND 2

Algorithm	Study-1		Study-2	
	Total cost (\$)	Simulation time (sec)	Total cost (\$)	Simulation Time (sec)
HDP	78895.5	1	78911	2.34
PSO	78895.5	1.3	78900	1.344
PSOC	78895.5	0.734	78899	0.734
CPSO	78895.5	0.75	78899	0.75
NPSO	78895.5	1.15	78900	1.172

C. *Study -3*

In this studied case, the ramp rate constraints of the generating units are taken into account along with the wind generation. For simplicity, the available wind power generation of tt he equivalent wind generator is assumed to be 400 MW for all time periods. The system up-spinning reserve requirement without considering wind power generation is assumed to be 300 MW. The generator ramp rate and startup ramp rate constraints are set at 60% of its rated capacity. The maximum up spinning reserve of any single thermal unit could not contribute more than 20% of its rated capacity. For this study, three different cases are considered as follows:

Case1:

In this case, the first-order model for calculation of additional up spinning reserve requirements is considered and for comparison purpose wind generator constraints and down spinning reserve requirement constraints is relaxed. Table-IV depicts the comparison of results of the proposed methods with HDP [7] for case1. It is observed that CPSO gives least cost while taking less time compared to the other approaches.

TABLE-IV
TOTAL COST AND SIMULATION TIME OF CASE-1

Algorithm	Total cost in $	Simulation time in Sec
HDP	58134	2.80
PSO	58102	1.8
PSOC	58100	1.2
CPSO	58100	1.145
NPSO	58100	1.162

Case2:

In this studied case, the first-order model for calculation of additional up spinning reserve requirements and down spinning reserve requirement is considered and for comparison purpose wind generator constraints are taken in to account. Table-V depicts the comparison of results of the proposed methods with HDP [7] for case-2. Table-VI gives the determined commitment schedule for this case. From this table it can be seen that the cost with HDF is higher than the PSO methods. However, all the version of PSO used give the same cost but the time of simulation is less with CPSO.

TABLE-V
TOTAL COST AND SIMULATION TIME OF CASE 2

	Case-2		Case-3	
Algorithm	Total cost ($)	Simulation time (sec)	Total cost ($)	Simulation Time (sec)
HDP	58233	6.64	58790	More than 7
PSO	57831	4.42	58631	5.5
PSOC	57831	3.85	58630	4.65
CPSO	57831	3.65	58630	4.20
NPSO	57831	4.12	58630	5.12

TABLE-VI
DETERMINED COMMITMENT SCHEDULE FOR CASE -2

Unit No.	Hour (1 to 24)
1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
4	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
5	1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 1 1 1 1 1
6	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
7	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
8	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
9	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
10	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Case 3:

In this case, the first-order model for calculation of additional up spinning reserve requirements and first-order model for calculation of down spinning reserve requirement are considered and for comparison purpose wind generator constraints are taken in to account. Table-V shows the comparison of results of the proposed methods with HDP [7] for case-3. For all the case studies, crazy PSO gives a better result and takes lesser simulation time compared to other methods.

VI. CONCLUSION

This paper presents four modified versions of Particle Swarm Optimization (PSO) techniques to solve wind-thermal coordination problem and a new pseudo code based algorithm is developed for handling equality constraints. A ten-unit test system is simulated to demonstrate the effectiveness of the proposed methods compared with the other methods. From the numerical results, it is found that the proposed PSO methods provide a better cost and take less simulation time compared to Hybrid Dynamic Programming (HDP) method. Moreover, the crazy PSO gives better results in cost and time compared to the other versions of PSO tested in this paper.

REFERENCES

[1] A. J. Wood and B. F. Wollenberg, *Power Generation Operation and Control*. New York: Wiley, 1984.

[2] C. L. Chen and S.-C. Wang, "Branch-and-bound scheduling for thermal generating units," *IEEE Trans. Energy Convers.*, vol. 8, no. 2, pp. 184–189, Jun. 1993.

[3] A. Merlin and P. Sandrin, "A new method for unit commitment at electricite De France," *IEEE Trans. Power App. Syst.*, vol. PAS-102, no. 5, pp. 1218–1225, May 1983.

[4] M. Piekutowski and I.A Rose, "A linear programming method for unit commitment incorporating generator configurations," *IEEE Trans. Power App. Syst.*, vol. PAS-104, no. 12, December 1985.

[5] A. G. Bakirtzis and V. Petridis, "A genetic algorithm solution to the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 11, no. 1, pp. 83–92, Feb. 1996.

[6] C-L Chen, "Optimal Wind–Thermal Generating Unit Commitment," *IEEE Trans. On energy conversion, Vol. 23, no.1, March 2008.*

[7] C-L Chen, "Simulated annealing-based Optimal Wind–Thermal Coordination scheduling," *IET Gener. Transm. Distribb., 2007, 1,(3), pp. 447-455.*

[8] *Bala Venkatesh, Peng Yu and H.B. Gooi, "Fuzzy MILP unit commitment incorporating Wind generators,"* IEEE Trans. Power Syst., vol. 23, No. 4, November 2008.

[9] Jong-Bae Park, Ki-Song Lee, Joong-Rin Shin, and Kwang Y. Lee, "A Particle Swarm Optimization for economic Dispatch With Nonsmooth Cost Functions," *IEEE Trans. Power Syst.*, vol. 20, No. 1, February 2005.

[10] Yuan Xiaohui , Yuan Yanbin ,Wang Cheng and Zhang Xiaopan, "An Improved PSO Approach for Profit-based Unit Commitment in Electricity Market" 2005 *IEEE/PES Transmission and Distribution Conference & Exhibition,* 2005.

[11] T. O. Ting, M. V. C. Rao, and C. K. Loo, "A Novel Approach for Unit Commitment Problemvia an Effective Hybrid Particle Swarm Optimization," *IEEE Trans. Power Syst.*, vol. 21, no. 1, February 2006

[12] Zwe-Lee Gaing, " Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints*," IEEE Trans. on Power Systems*, vol. 18, no. 3, pp. 1187-1195, August 2003.

BIOGRAPHIES

S. N. Singh is a Professor in the Department of Electrical Engineering, Indian Institute of Technology Kanpur, India. Presently, he is on leave from IIT Kanpur and working with Technical University of Denmark His research interests include power system restructuring, power system optimization & control and AI application to power system problems. He is a Fellow of IE (India), Fellow of IETE (India), and senior member of IEEE.

Jacob Østergaard is a Professor and Head of the Centre for Electric Technology, Technical University of Denmark. His research interests include integration of renewable energy, control architecture for future power system, and demand side. Professor Østergaard is serving in several professional organizations including the EU Smart Grids advisory council.

J. Yadagiri received M.Tech from Indian Institute of Technology Kanpur, India in 2009. His research interests include power system optimization & control.